Software Engineering

Trends in Class Decisions during Transitions in Myoelectric Control

SWE4913 Final Report

Version <2.0>
Created: 2023 MAY 01
Updated: 2023 JUNE 24

Grace Ashfield, 3388160
Supervised By: D MacIsaac, PhD

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Updated: 2023 JUNE 24 by Grace Ashfield

1 Focus

The purpose of this work is to develop a tool that collates and displays classifier decisions during transitions from one class to another in myoelectric control, aiming to identify common trends in classifier behavior. The motivation behind this research stems from the observation that while classifiers demonstrate high accuracy when trained and cross-validated offline using electromyography (EMG) data, their performance often does not translate to the same level of effectiveness when measured through usability metrics in controlling EMG-based assistive devices, such as myoelectric prostheses [1].

One plausible explanation for this performance discrepancy is that classifiers are typically trained using data collected during steady state contractions for each individual class [2]. However, real-world scenarios involving the use of assistive devices frequently involve dynamic contractions, including transitions from one class to another. Unfortunately, there has been limited research conducted to investigate the effects of this incongruence, creating a gap in our understanding [2]. Therefore, this work aims to address this gap and explore the impact of transitions on classifier performance in myoelectric control.

The existing literature in this field is scarce, and various aspects need to be explored to bridge this knowledge gap. Previous studies have proposed rejection techniques to ignore transition regions [3]. However, these techniques predominantly rely on decision confidence, and classifiers often exhibit high confidence even in incorrect decisions, particularly during transitions [3]. Other research efforts have focused on studying the transition problem and its implications, including challenges associated with training classifiers to include transitions as separate classes and the assignment of labels in training [4]. These challenges arise due to the large number of classes required for training, considering that each transition would need to be adequately represented.

In light of these considerations, our goal was to investigate the behavior of classifiers trained with steady state data when tested with dynamic contractions, with a specific focus on analyzing the classifier decisions during transition regions. By developing a tool that collates and displays classifier decisions during these transitions, we aimed to identify common trends and gain insights into the classifier's behavior in dynamic contractions. The analysis of classifier decisions in transition regions can provide valuable information about the challenges and limitations of current classifier approaches, ultimately leading to improvements in the design and implementation of EMG-based assistive devices.

In this paper, we present the development of a graphical user interface (GUI) that enables the visualization and analysis of classifier decisions on EMG data during transition regions. The GUI provides researchers and developers with the means to examine frames within transition regions and their predicted movements, facilitating the identification of patterns and trends in the classifier's decisions during transitions. By investigating these transition regions, we aim to shed light on the challenges and limitations associated with classifier performance in assistive device applications. Through this analysis, we hope to contribute to the development of improved usability metrics and enhance the functionality and user experience of EMG-based assistive devices.

Overall, this work strives to bridge the gap between offline classifier performance and real-time control in dynamic contractions. By studying the behavior of classifiers during transitions and identifying common trends, we seek to enhance our understanding of the challenges associated with classifier performance in assistive device applications. Through this investigation, we aim to pave the way for improvements in usability metrics and foster advancements in the design and implementation of EMG-based assistive devices.

2 Investigation

2.1 Tool Development

The development of the tool involved implementing a graphical user interface (GUI) using Python to visualize and analyze the predictions made by a classifier on electromyography (EMG) data during transitions between movement classes. The goal was to create a user-friendly tool that enables researchers and developers to gain insights into the behavior of the classifier during dynamic contractions, particularly during transition regions.

The GUI was built using the popular PyQt Python library, which provided the foundation for creating a visually appealing and interactive interface for users. These PyQt libraries allowed for the creation of tabular representations of frames within transitions regions. The tables were generated dynamically based on the classifier's predictions, displaying the transitions between movement classes and the corresponding uncertainties. The GUI provided interactive features, such as the ability to toggle between different table formats and navigate through the data for individual participants.

The GUI's main functionality allows researchers and developers to analyze frames within these regions and their predicted movements. By presenting the data in a tabular format, the tool enabled the identification of patterns and trends in the classifier's decisions during transitions. Each table represented the frames within transition regions from one state to all other states.

	NM	WF	WE	WP	WS	CG	HO	Frames
NM->WF	16%	12%	0%	23%	29%	6%	14%	1561
NM->WE	5%	0%	4%	50%	1%	24%	15%	2245
NM->WP	17%	2%	9%	9%	24%	7%	32%	2731
NM->WS	29%	3%	0%	33%	7%	10%	18%	1941
NM->CG	9%	13%	5%	42%	4%	12%	15%	1280
NM->HO	8%	2%	0%	60%	12%	11%	7%	1856

Figure 1: No Motion Table

As seen in Figure 1, the table has dimensions of 6x8, where rows represent transitions between states, and columns represent the possible states. Each row has a header cell that identifies the start and end state of the transition, while the column headers represent all possible states. The last column displays the total number of frames within transition regions. Additionally, users have the option to view the table in a 7x8 format, ensuring consistency across all tables. In this format, a new row is added to indicate that there was no possible transition from the start state to itself, and it is displayed in gray to differentiate it from other rows.

The percentages indicate the proportion of frames identified for each class relative to the total number of frames found in the last column of each row. For instance, when transitioning from No Motion to Wrist Flexion there are 1561 total frames within the transition region; 16% of the frames were classified as No Motion, 12% as Wrist Flexion, 0% as Wrist Extension, 23% as Wrist Pronation, 29% as Wrist Supination, 6% as Chuck Grip, and 14% as Hand Open.

The GUI offers several additional features to enhance its functionality. Users can choose different data sets for analysis, including the option to load individual participant data or aggregate data from multiple participants. This flexibility allows researchers to gain insights at both the individual level and the overall cohort level. The tool also employs colorization to draw attention to areas of confusion in the table, facilitating the quick identification of trends or outliers in the data.

Furthermore, the tool provides the capability to export data in multiple ways. Users can export the data to an Excel sheet, which includes both aggregate user data and individual participant data. Additionally, users can capture screenshots of their current view using the tool. These features are crucial for data sharing with collaborators, colleagues, or reviewers, as they allow for the easy distribution and utilization of the findings, contributing to the advancement of knowledge in the field.

The development of the tool leveraged Python's strengths in data manipulation, and data visualization to create a robust and user-friendly interface for viewing classifier decisions during transition regions in myoelectric control. The combination of Python's libraries and the carefully designed GUI resulted in a powerful tool that empowers researchers and developers in gaining valuable insights into the behavior of classifiers and improving the usability metrics of EMG-based assistive devices.

2.2 Experiment

2.2-a Data Set

The Raghu Dataset was made available by Shriram Raghu and consists of 43 sub- jects performing 7 classes of movement. Surface electromyography (sEMG) signals were recorded using six bipolar electrodes placed around the forearm, using a Delsys Trigno System. The signals were sampled at 2kHz with a 16-bit Analog-To-Digital converter [2]. The position of the hand was simultaneously recorded using a Leap Motion Controller to serve as ground truth for identifying transition regions.

For the training and testing protocol, participants performed ramp contractions followed by a steady-state contraction in different hand positions. The classes included Wrist Flexion (WF), Wrist Extension (WE), Wrist Pronation (WP), Wrist Supination (WS), Chuck Grip (CG), Hand Open (HO), and No Movement (NM). Each participant completed five trials, and the training data consisted of five repetitions of each class.

The test records involved continuous transitions from one class to another, generating 42 transitions in total (7 classes x 6 transitions). Participants were instructed to move randomly from one contraction to another and hold each contraction in steady state for 3 seconds. The Leap Motion position data was used to identify the bounds of transition regions based on hand orientation vector velocity, with a threshold to accommodate random fluctuations. Each participant completed six trials.

The study compared different Decision Stream Quality Improvement (DSQI) algorithms. The training and test records were segmented into overlapping frames of 160ms length with a 16ms increment. The LSF4 feature set was extracted from each frame. Three classifiers were trained: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM).

2.2-b Classification

LDA (Linear Discriminant Analysis) is a supervised learning algorithm used for classification tasks. It assumes that the data follows a Gaussian distribution and aims to find a linear combination of features that maximizes the separation between different classes [5]. LDA projects the data onto a lower-dimensional space while preserving the class separability. It computes class centroids and scatter matrices to determine the optimal projection direction. LDA is widely used in various fields, including pattern recognition, image processing, and bioinformatics.

To make predictions, LDA applies Bayes' rule, which involves calculating the posterior probability of a sample belonging to each class given its observed features [6]. The class with the highest posterior probability is then assigned to the sample. To perform this calculation, LDA uses the estimated parameters of the Gaussian distributions along with the prior probabilities of the classes, which can be determined from the training data.

LDA is a widely used classifier due to its simplicity and interpretability. It serves as a popular baseline model for comparison with more complex classifiers. Although LDA assumes linearity and the Gaussian distribution of data, it can still provide effective classification results in many practical scenarios.

2.2-c Collation

The GUI allows the user to load the previously collected data, as mentioned in section 2.2-a. The GUI identifies frames with lower confidence or uncertainty in their predictions, these frames are observed during transitions between movement classes. The data is loaded viewing all data collected from each participant, and the option is given to view individual data. When viewing individual participant data, the user will have the option to navigate to the preceding and proceeding data, while also having the option to select a participant's data from a dropdown list, or to type the desired participant into a search box.

The GUI displays frames within transition regions and their predicted movements in a tabular format. These tables enable users to analyze the classifier's decisions during transition regions and identify patterns or trends. Each table represents the frames within transition regions from one state to all other states. The format of each table is 6x8, with rows representing transitions between states and columns representing the possible states. The last column shows the total number of frames within transition regions. The percentages displayed in the tables indicate the proportion of frames identified for a class relative to the total number of frames found in the last column of each row. Additionally, users can choose to view the table in a 7x8 format, which ensures consistency across all tables. In this format, a new row is added to indicate that there is no possible transition from the start state to itself, and it is displayed in grey to distinguish it from other rows.

	NM	WF	WE	WP	WS	CG	HO	Frames
NM->WF	16%	12%	0%	23%	29%	6%	14%	1561
NM->WE	5%	0%	4%	50%	1%	24%	15%	2245
NM->WP	17%	2%	9%	9%	24%	7%	32%	2731
NM->WS	29%	3%	0%	33%	7%	10%	18%	1941
NM->CG	9%	13%	5%	42%	4%	12%	15%	1280
NM->HO	8%	2%	0%	60%	12%	11%	7%	1856

	NM	WF	WE	WP	WS	CG	HO	Frames
WF->NM	8%	3%	7%	23%	22%	24%	14%	5801
WF->WE	30%	4%	4%	17%	15%	23%	7%	6358
WF->WP	31%	3%	18%	5%	12%	21%	10%	7870
WF->WS	44%	5%	5%	21%	5%	9%	11%	5254
WF->CG	41%	5%	6%	17%	17%	8%	7%	4800
WF->HO	25%	3%	8%	29%	18%	13%	4%	7745

	NM	WF	WE	WP	WS	CG	HO	Frames
WE->NM	4%	7%	4%	50%	9%	13%	13%	6126
WE->WF	19%	5%	5%	42%	10%	11%	8%	5741
WE->WP	23%	4%	12%	5%	13%	12%	31%	3537
WE->WS	14%	10%	4%	43%	4%	10%	15%	6585
WE->CG	16%	15%	4%	45%	7%	3%	10%	6170
WE->HO	10%	18%	4%	42%	8%	12%	5%	7343

	NM	WF	WE	WP	WS	CG	HO	Frames
WP->NM	6%	0%	13%	14%	26%	33%	8%	3901
WP->WF	28%	2%	5%	6%	25%	25%	9%	4966
WP->WE	23%	2%	10%	9%	6%	42%	8%	2749
WP->WS	41%	0%	13%	7%	2%	28%	9%	3901
WP->CG	41%	2%	18%	9%	10%	13%	7%	2359
WP->HO	24%	1%	7%	21%	21%	22%	5%	4237

	NM	WF	WE	WP	WS	CG	HO	Frames
WS->NM	19%	8%	4%	37%	6%	14%	13%	3308
WS->WF	61%	6%	0%	13%	12%	2%	6%	5998
WS->WE	49%	4%	3%	21%	6%	9%	8%	5493
WS->WP	50%	2%	5%	9%	9%	4%	21%	6096
WS->CG	55%	6%	1%	20%	6%	5%	7%	5812
WS->HO	43%	3%	1%	32%	11%	2%	7%	6035

	NM	WF	WE	WP	WS	CG	HO	Frames
CG->NM	4%	3%	2%	47%	7%	8%	28%	6396
CG->WF	34%	4%	0%	28%	13%	6%	15%	4303
CG->WE	22%	2%	4%	41%	3%	8%	19%	3950
CG->WP	25%	3%	4%	7%	9%	6%	46%	4081
CG->WS	27%	5%	1%	37%	2%	5%	23%	5440
CG->HO	25%	9%	1%	44%	10%	7%	5%	4095

	NM	WF	WE	WP	WS	CG	HO	Frames
HO->NM	5%	1%	1%	49%	17%	19%	8%	4564
HO->WF	36%	5%	0%	30%	12%	8%	8%	5790
HO->WE	22%	0%	6%	40%	9%	16%	6%	5613
HO->WP	27%	0%	7%	11%	14%	8%	32%	3781
HO->WS	37%	1%	1%	40%	3%	6%	12%	5825
HO->CG	38%	2%	2%	34%	9%	7%	7%	5099

Figure 2: Graphical User Interface with Data Loaded

By utilizing this GUI, researchers and developers can gain insights into the classifier's behavior during dynamic contractions and specifically focus on the predictions made during transition regions. Its ability to identify frames within transition regions and present them in tabular format facilitated the identification of patterns and trends, aiding in the understanding of the classifier's behavior. The insights gained from this analysis contribute to the improvement of usability metrics in EMG-based assistive devices, furthering their applicability and impact in the field.

2.2-d Results and Discussion

The analysis revealed that during transitions, classifiers often exhibit high confidence even in incorrect decisions. This finding highlights the need for improved techniques to handle transitions and mitigate the impact of misclassifications. The GUI facilitated the identification of frames within transition regions, enabling researchers to focus on these critical decision points and develop strategies to improve classifier performance during transitions. By examining the provided tables and observing examples of transitions in the training data, ideally, we should see that the distribution of percentages should concentrate around the motion that is being initiated or terminated. However in our observations, we see this is not always the case.

	NM	WF	WE	WP	WS	CG	HO	Frames
NM->NM								
NM->WF	16%	12%	0%	23%	29%	6%	14%	1561
NM->WE	5%	0%	4%	50%	1%	24%	15%	2245
NM->WP	17%	2%	9%	9%	24%	7%	32%	2731
NM->WS	29%	3%	0%	33%	7%	10%	18%	1941
NM->CG	9%	13%	5%	42%	4%	12%	15%	1280
NM->HO	8%	2%	0%	60%	12%	11%	7%	1856

Table 1: No Motion to Other States

One notable observation is that transitions from no motion (NM) to other transitions, as this data was trained with ramp contractions, we would expect to see more concentration in either the NM column, or the column for the state that is being transitioned to. However, the analysis reveals a more even distribution of predictions, with wrist pronation (WP) being the most common transition, as seen in Table 1. This discrepancy suggests a tendency of the classifier to predict WP regardless of the intended motion. Additionally, a closer examination of the NM table reveals that the average number of frames associated with NM is smaller compared to other tables, indicating that transitions only occur once a different motion is detected.

Understanding these biases and tendencies becomes valuable in refining the training process and developing strategies to address them. For example, knowledge of the classifier's inclination towards specific classes during transitions can inform the adaptation scheme used in training. By weighing down the biasing class significantly or implementing a rejection scheme, the classifier can be trained to mitigate these biases and make more accurate predictions. Rejection, in this context, refers to setting a confidence threshold and only accepting predictions when the confidence surpasses the threshold.

	NM	WF	WE	WP	WS	CG	HO	Frames
NM->WF	16%	12%	0%	23%	29%	6%	14%	1561
NM->WE	5%	0%	4%	50%	1%	24%	15%	2245
NM->WP	17%	2%	9%	9%	24%	7%	32%	2731
NM->WS	29%	3%	0%	33%	7%	10%	18%	1941
NM->CG	9%	13%	5%	42%	4%	12%	15%	1280
NM->HO	8%	2%	0%	60%	12%	11%	7%	1856

	NM	WF	WE	WP	WS	CG	HO	Frames
WF->NM	8%	3%	7%	23%	22%	24%	14%	5801
WF->WE	30%	4%	4%	17%	15%	23%	7%	6358
WF->WP	31%	3%	18%	5%	12%	21%	10%	7870
WF->WS	44%	5%	5%	21%	5%	9%	11%	5254
WF->CG	41%	5%	6%	17%	17%	8%	7%	4800
WF->HO	25%	3%	8%	29%	18%	13%	4%	7745

	NM	WF	WE	WP	WS	CG	HO	Frames
WE->NM	4%	7%	4%	50%	9%	13%	13%	6126
WE->WF	19%	5%	5%	42%	10%	11%	8%	5741
WE->WP	23%	4%	12%	5%	13%	12%	31%	3537
WE->WS	14%	10%	4%	43%	4%	10%	15%	6585
WE->CG	16%	15%	4%	45%	7%	3%	10%	6170
WE->HO	10%	18%	4%	42%	8%	12%	5%	7343

	NM	WF	WE	WP	WS	CG	HO	Frames
WP->NM	6%	0%	13%	14%	26%	33%	8%	3901
WP->WF	28%	2%	5%	6%	25%	25%	9%	4966
WP->WE	23%	2%	10%	9%	6%	42%	8%	2749
WP->WS	41%	0%	13%	7%	2%	28%	9%	3901
WP->CG	41%	2%	18%	9%	10%	13%	7%	2359
WP->HO	24%	1%	7%	21%	21%	22%	5%	4237

	NM	WF	WE	WP	WS	CG	HO	Frames
WS->NM	19%	8%	4%	37%	6%	14%	13%	3308
WS->WF	61%	6%	0%	13%	12%	2%	6%	5998
WS->WE	49%	4%	3%	21%	6%	9%	8%	5493
WS->WP	50%	2%	5%	9%	9%	4%	21%	6096
WS->CG	55%	6%	1%	20%	6%	5%	7%	5812
WS->HO	43%	3%	1%	32%	11%	2%	7%	6035

	NM	WF	WE	WP	WS	CG	HO	Frames
CG->NM	4%	3%	2%	47%	7%	8%	28%	6396
CG->WF	34%	4%	0%	28%	13%	6%	15%	4303
CG->WE	22%	2%	4%	41%	3%	8%	19%	3950
CG->WP	25%	3%	4%	7%	9%	6%	46%	4081
CG->WS	27%	5%	1%	37%	2%	5%	23%	5440
CG->HO	25%	9%	1%	44%	10%	7%	5%	4095

	NM	WF	WE	WP	WS	CG	HO	Frames
HO->NM	5%	1%	1%	49%	17%	19%	8%	4564
HO->WF	36%	5%	0%	30%	12%	8%	8%	5790
HO->WE	22%	0%	6%	40%	9%	16%	6%	5613
HO->WP	27%	0%	7%	11%	14%	8%	32%	3781
HO->WS	37%	1%	1%	40%	3%	6%	12%	5825
HO->CG	38%	2%	2%	34%	9%	7%	7%	5099

Figure 3: LDA Data Set

In the analysis of the transition tables from our dataset in Figure 3, several interesting observations can be made. In the Wrist Flexion table, the predictions are fairly dispersed, suggesting a lack of clear dominance or bias towards any particular class. This indicates that Wrist Flexion transitions pose a challenge for the classifier, potentially requiring further investigation and refinement.

Moving to the Wrist Extension table, regardless of the state it transitions to, there is a consistent tendency to predict Wrist Pronation. This suggests a bias or preference of the classifier towards predicting Wrist Pronation during Wrist Extension transitions.

Exploring the Wrist Pronation table uncovers some individual confusions. Specifically, transitions from Wrist Pronation to Wrist Supination and Chuck Grip often result in predictions of No Motion. In the Wrist Supination table, it becomes evident that the classifier often predicts No Motion. This observation is visually striking as the column representing No Motion draws immediate attention. This finding highlights the ability of the tool to assess specific motion-to-motion combinations. It also emphasizes that the prediction of No Motion may be a preferable outcome compared to predicting the wrong movement class.

Analyzing the Chuck Grip table reveals a relatively random confusion pattern. However, there is a noticeable tendency towards predicting Wrist Pronation as the most frequent class, followed by No Motion and Hand Open. This information provides insights into the classifier's behavior during Chuck Grip transitions, indicating certain recurring predictions.

Examining the Hand Open table, we observe that it weakly predicts No Motion and Wrist Pronation. These two classes seem to be the primary choices when transitioning from Hand Open. This insight can be valuable for further research and algorithmic improvements, as it highlights the tendencies and preferences of the classifier in specific transition scenarios.

It is important to note that these results are specific to the classifier and feature set used in this analysis. Different combinations of classifiers and feature sets would require similar analyses to uncover their respective biases and tendencies.

These observations from the transition tables provide valuable insights into the behavior of the classifier during dynamic contractions. They offer guidance for refining the training process, augmenting feature selection, or exploring alternative classification algorithms to better handle transitions. By leveraging this information, future studies can focus on developing advanced classification algorithms that are specifically tailored to address the challenges associated with transition regions, ultimately leading to improved control and usability of EMG-based assistive devices.

3 Contributions

This work makes significant contributions to the field of myoelectric control by developing a GUI that collates and displays classifier decisions during transitions in myoelectric control. This tool facilitates the analysis of patterns and trends in the behavior of classifiers during transition regions, allowing researchers to gain a more comprehensive understanding of the data being collected and processed.

The GUI serves as a user-friendly interface for researchers and developers to gain insights into the behavior of classifiers during dynamic contractions, where transitions between movement classes occur. By visualizing the classifier's decisions in tabular format, the tool allows for the identification of patterns in levels of uncertainty, enabling researchers to better understand the challenges and limitations associated with classifier performance during transitions.

By investigating the behavior of classifiers during dynamic contractions, specifically during transition regions, this work aims to bridge this gap and provide a deeper understanding of the challenges faced in real-world scenarios. Moreover, this work contributes to the development of improved usability metrics for EMG-based assistive devices. The ability to analyze patterns and uncertainties during transitions provides valuable information that can lead to advancements in usability metrics, ultimately enhancing the functionality and user experience of EMG-based assistive devices.

4 References

[1] J. Chang, A. Phinyomark, S. Bateman, and E. Scheme, "Wearable EMG-Based Gesture Recognition Systems During Activities of Daily Living: An Exploratory Study," in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada: IEEE, Jul. 2020, pp. 3448–3451, ISBN: 9781728119908. DOI: 10 . 1109 / EMBC44109 . 2020 . 9176615.

[2] Tallam Puranam Raghu, Shriram; MacIsaac, Dawn; Scheme, Erik (2023): Decision-change Informed Rejection Improves Robustness in Pattern Recognition-based Myoelectric Control. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.22492711.v1

[3] E. J. Scheme, B. S. Hudgins, and K. B. Englehart, "Confidence- Based Rejection for Improved Pattern Recognition Myoelectric Con- trol," IEEE Transactions on Biomedical Engineering, vol. 60, no. 6, pp. 1563–1570, Jun. 2013, ISSN: 0018-9294, 1558-2531. DOI: 10. 1109/TBME.2013.2238939.

[4] Jonathon W Sensinger, Blair A Lock, and Todd A Kuiken, Adaptive pattern recognition of myoelectric signals: Exploration of conceptual framework and practical algorithms, (2009).

[5] J. Meneley, "Title of Thesis," Master's thesis, University of New Brunswick, 2020.

[6] R. Herbei and M. H. Wegkamp, "Classification with reject option", Can. J. Stat., vol. 4, no. 4, pp. 709-721, 2006.